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Pedagogical framework for hybrid intelligent feedback

Seyyed Kazem Banihashem [a], Omid Noroozi [b], Hassan Khosravi [c], Christian D. Schunn [d] and Hendrik Drachsler [a,e]

[a]Open Universiteit, Heerlen, The Netherlands; [b]Wageningen University and Research, Wageningen, The Netherlands; [c]University of Queensland, Brisbane, Australia; [d]University of Pittsburgh, Pittsburgh, Pennsylvania, USA; [e]DIPF Leibniz Institute & Goethe University, Frankfurt am Main, Germany

ABSTRACT

Generative AI (GenAI) has gained attention as a new feedback source in education because it can generate human-like text. However, its use in feedback lacks a strong pedagogical framework, which is necessary for effective implementation. This paper addresses this gap. It outlines human-centered feedback challenges, and then explores human and artificial cognition differences, highlighting the need for hybrid intelligence. Next, it positions GenAI feedback within feedback theory and proposes a definition for GenAI feedback. The paper conceptualizes the role of GenAI feedback as either an independent source or as part of a collaborative process with humans referred to as "Hybrid Intelligent Feedback". Building on this conceptualization, it discusses the approaches and principles of hybrid intelligent feedback and then proposes a pedagogical framework that outlines the implementation steps for hybrid intelligent feedback. The paper concludes by describing the pedagogical framework and outlining recommendations for future research on hybrid intelligent feedback.

KEYWORDS
Artificial intelligence; artificial cognition; feedback; generative AI; hybrid intelligent feedback; human-AI collaboration

Introduction

Generative Artificial Intelligence (GenAI) technologies, powered by advanced large language models (LLMs), are revolutionising fields like education. Tools such as ChatGPT and Gemini demonstrate exceptional accuracy and reasoning, surpassing human intelligence in various areas without task-specific development (Kasneci et al., 2023). This marks the rise of 'artificial cognition', reshaping learning experiences (Siemens et al., 2022). In education, GenAI is driving a transformative shift, redefining how students learn, teachers teach, and institutions function, making its integration an inevitable step forward (Yan et al., 2024). GenAI tools are rapidly being adopted in higher education due to their accessibility. Teachers use tools like ChatGPT to create lesson plans, quizzes, and summarise student responses (Kasneci et al., 2023), while students rely on them for research, article summaries, essay drafting, and personalised tutoring (Farrokhnia et al., 2024). There

CONTACT Seyyed Kazem Banihashem kazem.banihashem@ou.nl Open Universiteit, Valkenburgerweg 177, Heerlen 6419 AT, The Netherlands

have also been attempts to unite students, teachers, and AI to work in partnership for educational content creation (Khosravi et al., 2023).

The rapid expansion of GenAI in education highlights the urgent need for its alignment with sound pedagogical principles. Without this grounding, risks include technological determinism (Smith & Marx, 1994) – the belief that technology alone can shape or dictate educational outcomes, use of opaque, black-box predictive models for decision-making (Khosravi et al., 2022), and neglecting the crucial role of how teachers and students use these tools. This could undermine student outcomes by sidelining creativity, empathy, and contextual understanding (Darvishi et al., 2024). To unlock GenAI's full potential, it must be thoughtfully integrated into pedagogical practices (Chen et al., 2020; Díaz & Nussbaum, 2024) ensuring it complements rather than replaces human-centred education. This approach aligns with the growing emphasis on human-AI collaboration and hybrid intelligence, which combines human and artificial cognition to achieve outcomes beyond the capability of either alone (Järvelä et al., 2023; Molenaar, 2022).

One promising area for human-AI collaboration in education is the use of GenAI for feedback, known as 'GenAI feedback'. A global debate is emerging about its credibility as a valid feedback source (Banihashem et al., 2024; Er et al., 2024; Wan & Chen, 2024). Current literature highlights the rapid expansion of GenAI feedback across diverse learning tasks (Escalante et al., 2023; Guo et al., 2024; Steiss et al., 2024). However, this adoption often lacks robust pedagogical frameworks to guide its responsible and effective use in education. Developing such frameworks can ensure thoughtful integration, foster trust among teachers and students, and encourage meaningful engagement with GenAI feedback (Kitto et al., 2023).

This gap highlights the need to conceptualise GenAI feedback by grounding it in established feedback theories and theorising Hybrid Human-AI collaboration for intelligent feedback. To do this, the paper begins by examining traditional, human-centred feedback – its definitions, phases, features, and historical challenges – to provide a foundation for understanding GenAI feedback. It then explores the distinctions between human and artificial cognition, illustrating their complementary roles in feedback processes and emphasising the value of hybrid intelligence, where human and AI collaboration achieves outcomes neither could accomplish alone. Building on this, we define GenAI feedback, propose a theoretical framework, outline its potential roles, and advocate for hybrid intelligence integration. We also address the opportunities and challenges of GenAI feedback in a hybrid intelligence context. Finally, we offer a roadmap for advancing research to ensure the responsible and effective integration of hybrid human-AI intelligence feedback in education.

Human-centred feedback

Feedback in education has traditionally been human-centred, with humans as the sole source of intelligence and it is widely recognised as a key strategy for improving learning processes and outcomes (Hattie & Timperley, 2007). Research highlights its significant impact on learning, motivation, academic performance, engagement, collaboration, and self-regulation (e.g. Banihashem et al., 2022; Shute, 2008). Feedback has been defined in multiple ways. Ramaprasad (1983) describes it as information addressing the gap between current and desired performance. Boud and Molloy (2013) view it as a reflective process that enables learners to assess and improve their work. D. J. Nicol and Macfarlane-Dick (2006) advocate for feedback as a dialogue that fosters self-regulated learning, while Black and Wiliam (2009) emphasise its role in formative assessment, linking feedback directly to actionable goals. Sadler (1989) highlights its purpose in reducing the gap between current understanding and desired objectives. Among these definitions, Hattie and Timperley's (2007) widely accepted definition unifies these perspectives, describing feedback as information provided by an agent to improve a person's skills or knowledge in a specific task, aligning performance with intended outcomes.

Traditionally, the human agents for feedback have been teachers, peers, and the learners themselves leading to three main feedback sources: teacher feedback, peer feedback, and learners' feedback on their own performance, called internal feedback (D. Nicol, 2021), or self-feedback (see the left half of Figure 1). Feedback normally reflects on three aspects of the performance: What is the current state of the task (where the learner is now); what is the desired state of the task (where the learner is going); and how to get there? (Black & Wiliam, 2009). This also aligns with Hattie and Timperley's (2007) feedback model, where '*Feedback*' addresses the question 'Where is the learner now?', '*Feed Up*' focuses on 'Where is the learner going?', and '*Feed Forward*' emphasises 'How to get there?'. Effective feedback incorporates several essential elements, often categorised as affective, cognitive, and constructive (Noroozi et al., 2023; Patchan et al., 2016). Affective features involve praise, positive reinforcement, and compliments that motivate learners and encourage them to engage with the feedback constructively. Cognitive features focus on providing a clear description of the task and pinpointing specific issues or areas that require improvement. Constructive features emphasise actionable suggestions for improvement, accompanied by detailed plans for implementing these changes (Noroozi et al., 2023). Timeliness and personalisation are also crucial for feedback to be effective (Carless et al., 2011; Pardo et al., 2019). Feedback given in real-time allows learners to address issues while the task is still fresh, and personalised feedback tailored to their needs enhances its relevance and impact. The quality, timing, and personalisation of feedback significantly influence whether learners accept and act on it (X. Gao et al., 2023;

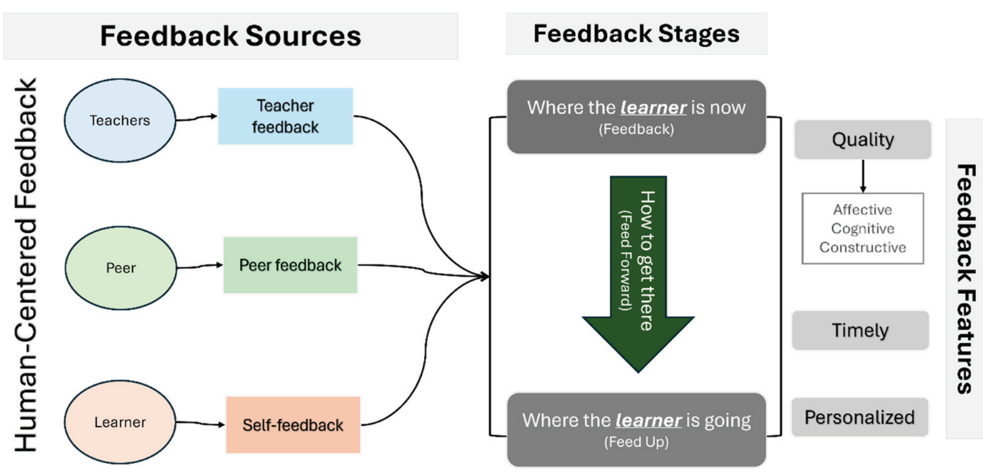

Figure 1. Human-centred feedback (adapted from Black & Wiliam, 2009).

Patchan et al., 2016). Without these characteristics, feedback is less likely to be embraced or effectively applied (see Figure 1).

Each human feedback source encounters unique challenges in delivering effective feedback. Teachers, despite being well-trained to provide high-quality feedback, often face difficulties in offering timely and personalised responses due to increasing workloads and growing class sizes in higher education (Er et al., 2021). Peer feedback, while offering timeliness and personalisation, is often limited by peers' lack of domain-specific expertise, making it harder to address nuanced task-related issues. As a result, peer feedback tends to focus on surface-level aspects like language or communication quality, neglecting deeper content issues (Y. Gao et al., 2019). Additionally, students may distrust their peers' competence, leading to scepticism about the feedback and reluctance to fully engage with or act upon it (Noroozi et al., 2023). Self-feedback, where learners assess their own performance against reference standards (D. Nicol, 2021), presents further challenges. Effective self-feedback demands strong self-regulation and high cognitive and metacognitive awareness. However, students with weaker performance levels often struggle with accurate self-assessment, a phenomenon linked to the Dunning-Kruger effect (Dunning, 2011). Without these critical skills, students may find it difficult to evaluate their progress accurately or make meaningful adjustments to their learning strategies.

While teacher, peer, and self-feedback continue to face challenges, advanced technologies like GenAI are increasingly playing a pivotal role in improving feedback systems by supporting and facilitating high-quality, timely, and personalised responses (Banihashem et al., 2022; Bauer et al., 2023; Er et al., 2024; Guo et al., 2024). The next section examines human and artificial cognition, highlighting the concept of hybrid intelligence. We then define GenAI feedback, its theoretical basis, and its roles, with an emphasis on hybrid intelligent feedback. This is followed by a discussion of hybrid intelligent feedback approaches and principles, leading to the proposal of a pedagogical framework. The paper concludes by proposing a research agenda and conclusion.

Human cognition vs artificial cognition: Call for hybrid intelligence

John McCarthy, a pioneer in AI, defined it as 'the science and engineering of making intelligent machines, especially intelligent computer programs' (McCarthy, 2007, p. 2). Here, 'intelligent' refers to a machine's ability to perform cognitive functions like learning, reasoning, and problem-solving. From this perspective, AI is considered a system capable of performing cognitive activities similar to human cognition, such as sense-making and decision-making, but it operates within distinct and separate cognitive systems from humans, often achieving strong performance in ways that are very different from how humans think (Siemens et al., 2022). GenAI, a subset of AI, focuses on generating new, original content by learning patterns from existing data. Using deep learning techniques, systems like GPT models can produce text, images, music, and other media in a way that approximates human creativity and comprehension (Brown et al., 2020).

While both human and artificial cognition involve cognitive processing, they represent fundamentally different systems shaped by their unique biological and digital architectures. Human cognition emerges from the parallel activity of neurons and synapses, characterised by emotional awareness, consciousness, intuition, and self-reflection

(Siemens et al., 2022). In contrast, artificial cognition relies on sequential symbol manipulation through algorithms and data processing, inspired by biological systems but lacking emotion, consciousness, or subjective experience (Korteling et al., 2021). Recognising the strengths and limitations of each system is essential for fostering hybrid intelligence in an AI-driven world (Markauskaite et al., 2022).

Human cognition is deeply influenced by lived experiences, culture, and social interactions (Siemens et al., 2022). Humans can think abstractly, adapt knowledge across contexts, and use creativity and moral reasoning. Learning is experiential and cumulative, relying on sensory input, trial and error, and social interactions (Piaget, 1954). Jean Piaget's work on cognitive development emphasised human learning's adaptive nature, where individuals adjust their understanding through new experiences, making cognition highly generalisable and enriched by common sense and contextual awareness (Siemens et al., 2022).

Artificial cognition relies on algorithms, machine learning, and data analysis, with systems like deep learning models enabling efficient pattern recognition and data processing (LeCun et al., 2015). However, these systems are often task-specific and struggle to generalise beyond their training (Binz & Schulz, 2023). While AI can surpass humans in processing speed and accuracy in areas like image classification and natural language processing, it lacks adaptability to novel, unforeseen circumstances (Siemens et al., 2022). This limitation is evident in AI's struggle to understand context, a challenge exemplified by John McCarthy's efforts to develop AI with common sense, which remains unresolved (Nezhurina et al., 2024).

A key distinction between human and artificial cognition lies in their approaches to learning and problem-solving. Humans engage in explicit reasoning, employing logic and mental simulations within working memory to solve complex problems (Shiffrin & Mitchell, 2023). In contrast, AI systems like GPT-3 are designed to predict outputs, such as the next word in a sequence, without engaging in deep reasoning or causal understanding. AI's reliance on statistical correlations, rather than active exploration and hypothesis testing, limits its ability to perform causal reasoning, a hallmark of human cognition (Binz & Schulz, 2023). Adaptability is another critical difference. Humans can transfer knowledge across contexts and draw on prior experiences to tackle novel challenges. AI systems, however, remain restricted to the specific domains they were trained in, lacking the flexibility to generalise effectively. This rigidity highlights AI's lack of true understanding and its limitations as an intelligent system (Searle, 1980).

In summary, human cognition and artificial cognition are shaped by fundamentally different processes. Recognising these differences is essential for effectively integrating AI into educational settings, where hybrid intelligence can enhance feedback by combining the complementary strengths of human and artificial cognition (Molenaar, 2022). Therefore, by employing hybrid intelligence, educational settings can benefit from a balanced application of human judgement and AI efficiency.

GenAI feedback: Definition, underlying theory, and roles

Building on Hattie and Timperley's (2007) feedback definition, we define GenAI feedback as '*Information generated by a GenAI agent about certain aspects of a learner's understanding or performance*'. While the goal remains to improve the learner's understanding

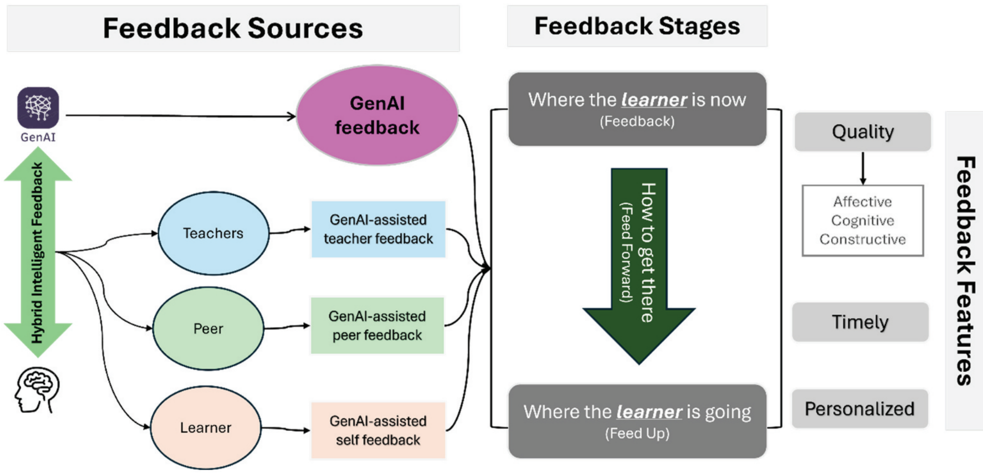

Figure 2. Human-GenAI collaboration as feedback sources (building upon Black & Wiliam, 2009).

or performance, the source shifts from human to GenAI. Grounded in Black and Wiliam's (2009) formative assessment theory, GenAI feedback addresses the three essential questions of effective feedback: Where is the learner going? Where are they now? How can they get there? Traditionally, these questions are addressed by teachers, peers, and learners, each with specific roles (Black & Wiliam, 2009). In a hybrid intelligence system, we propose that GenAI can enhance feedback provision by taking on two key main roles: GenAI as an independent feedback source and GenAI in collaboration with humans so-called hybrid intelligent feedback (see Figure 2).

GenAI as an independent feedback source

GenAI can act as an independent feedback source, complementing traditional feedback providers – teachers, peers, and learners – by guiding learners through the three formative assessment stages: Where is the learner going? Where is the learner now? How can they get there? In this role, GenAI delivers feedback directly based on task-specific prompts or questions. For example, in essay writing, students might use a GenAI tool like ChatGPT to review their work, receive evaluations on content, grammar, coherence, and structure, and obtain actionable recommendations for improvement. In this scenario, GenAI provides feedback independently, without human feedback input. Research by Escalante et al. (2023) shows comparable learning outcomes for students receiving GenAI or human feedback, with no significant preference difference, supporting its integration in tasks like essay writing. However, this role does not imply replacing teacher, peer, or self-feedback. Instead, GenAI feedback often complements these sources, enriching the feedback process. Studies by Banihashem et al. (2024) and Escalante et al. (2023) highlight the complementary nature of GenAI feedback, showing how GenAI feedback can supplement human feedback.

A growing body of research supports adding GenAI feedback alongside human feedback. Banihashem et al. (2024) found that ChatGPT feedback on essays was more descriptive and style-focused, while peer feedback addressed specific content issues, suggesting a complementary approach. Steiss et al. (2024) reported modest quality differences between GenAI and human feedback but highlighted the time-saving benefits of GenAI, proposing ChatGPT as an effective and efficient evaluative tool.

Human-GenAI collaboration: Towards hybrid intelligent feedback

In Figure 3, we present a conceptual framework that illustrates a spectrum of approaches to hybrid intelligent feedback, ranging from fully human-generated feedback to fully GenAI-generated feedback. This framework outlines how humans and GenAI can collaborate in various configurations to optimise feedback processes in educational and professional contexts. The spectrum highlights how feedback generation can evolve with increasing integration and reliance on GenAI, while still retaining human involvement as needed for enrichment and oversight.

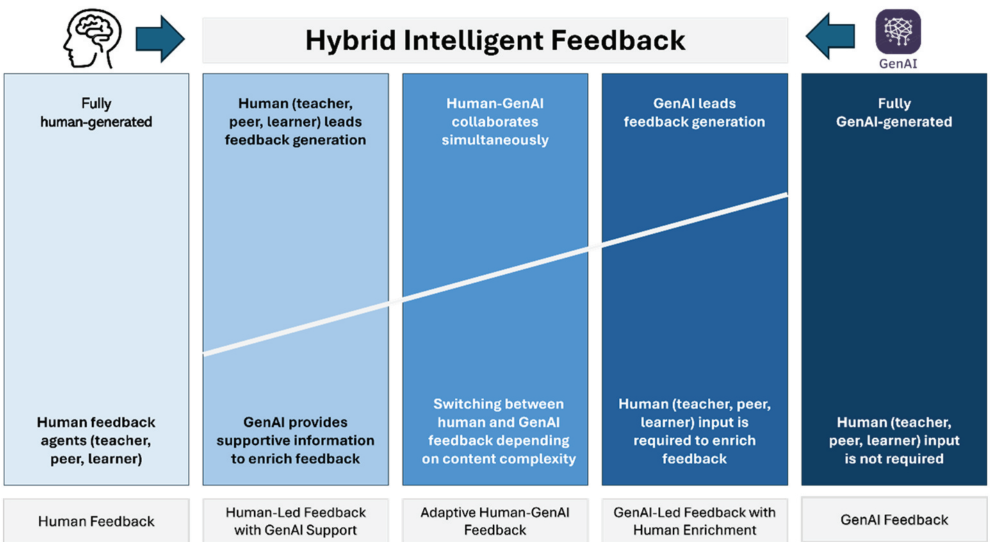

Figure 3. Conceptual framework of hybrid intelligent feedback approaches (inspired by Molenaar, 2022).

The spectrum begins with *Fully Human-Generated Feedback*, where feedback is created solely by human agents – teachers, peers, or learners – without any involvement from GenAI. At the other end lies *Fully GenAI-Generated Feedback*, in which feedback is entirely generated by GenAI without any human input. Between these two extremes, three intermediate approaches represent the core of hybrid intelligent feedback, blending human and GenAI contributions to various degrees:

> *Human-Led Feedback with GenAI Support*: In this approach, humans (teachers, peers, or learners) take the lead in providing feedback, while GenAI plays a supplementary role by offering additional insights to enhance the quality of the feedback. For example, a teacher might focus on evaluating the content and argumentation in a student's

essay, while GenAI identifies grammar errors, improves sentence structures, or suggests stylistic adjustments. This setup ensures that human expertise remains at the forefront, with GenAI acting as an assistive tool to refine or augment the feedback process. A study from Guo et al. (2024) is an example of using AI as a support to human-generated (peer) feedback. This study integrated an AI chatbot, Eva, into an online peer review system to support students in generating feedback. The chatbot provides two types of assistance: prompting and feedback. The prompting feature offers tips to help students craft high-quality comments. The results showed that students who used Eva provided higher-quality feedback and demonstrated greater improvements in writing ability compared to those who did not.

Adaptive Human-GenAI Feedback: This approach represents a dynamic partnership between humans and GenAI, where both contribute based on the complexity and nature of the task. Feedback generation becomes a flexible, collaborative process, with roles switching seamlessly between human and GenAI depending on the demands of the content. For instance, when evaluating a highly technical piece, GenAI might provide detailed, data-driven feedback on factual accuracy, while humans focus on subjective elements such as tone and intent. This adaptability ensures a more comprehensive and context-sensitive feedback mechanism. Current research has not yet largely focused on adaptive human-GenAI feedback. Bai and Nordin (2025) explored a human-AI collaborative feedback approach in which students could receive both AI and teacher feedback to enhance EFL students' writing performance where AI could focus on a more narrow range of issues. Although they did not specify the exact nature of how the feedback varied by source, the findings indicate that human-AI feedback significantly improves writing by providing timely and detailed insights, leading to enhanced language accuracy, complexity, and fluency.

GenAI-Led Feedback with Human Enrichment: In this approach, GenAI takes the lead in generating the initial feedback, while humans step in to review, refine, and contextualise it as needed. This approach leverages the efficiency and speed of GenAI while ensuring that human judgement adds a layer of nuance and contextual relevance. For example, GenAI might provide detailed feedback on a coding assignment, identifying errors and suggesting optimisations, while the teacher ensures the suggestions align with the learning goals and the student's proficiency level. A study by Wan and Chen (2024) is an example of this approach where teachers review and adjust GenAI-generated feedback. In this study, GPT-3.5 was iteratively trained to provide feedback on students' written tasks. Only 30% of AI-provided feedback statements needed significant modification from an instructor before being ready to be passed on to students.

These hybrid approaches highlight the potential of human-GenAI collaboration to create a feedback process that is both efficient and enriched with human insights. By leveraging the strengths of both humans and AI, this framework allows for tailored, adaptive, and high-quality feedback that meets diverse educational and professional needs.

Informed by Molenaar's (2022) conceptualisation of hybrid human-AI systems, we argue that the following principles define effective hybrid intelligent feedback (see Figure 4):

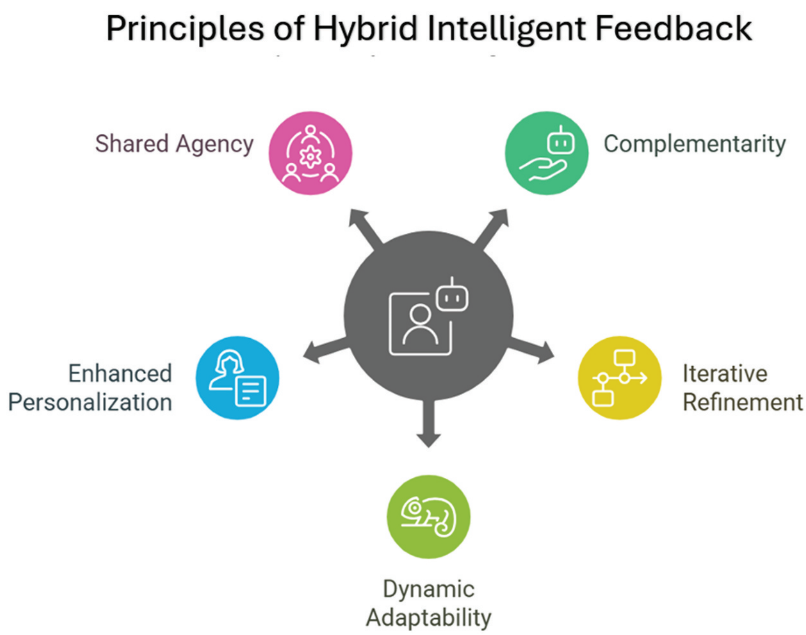

Figure 4. Principles of hybrid intelligent Feedback.

Complementarity: Hybrid intelligent feedback systems should capitalise on the respective strengths of humans and AI. GenAI can provide timely feedback and offer data-driven insights for routine tasks, while humans can enrich feedback with contextual depth, creativity, and emotional sensitivity. This duality within hybrid feedback is crucial for complex educational contexts where adaptability and nuanced understanding are key.

Iterative refinement: Hybrid intelligent feedback systems thrive on continuous improvement through iterative cycles. GenAI outputs serve as an initial layer of feedback, refined further by human contributions. Conversely, human feedback can be enhanced by GenAI-generated suggestions, creating a dynamic interplay that elevates feedback quality and relevance with each iteration.

Dynamic adaptability: Effective hybrid intelligent feedback systems should involve a dynamic adaptation process that tailors outputs to the evolving needs of learners and the context of the task. For instance, GenAI can assist teacher or peer feedback by prioritising specific aspects of feedback, such as critical thinking or technical skills, based on learner profiles.

Enhanced personalisation: By integrating GenAI's scalability with human understanding of individual learner needs, hybrid intelligent feedback systems can offer tailored support even in large-class settings. This personalised approach aligns with the growing emphasis on learner-centric pedagogies in modern education.

Shared agency: In feedback contexts, shared agency means learners, teachers, and GenAI tools collaboratively shape the feedback process, allowing learners to take ownership of their improvement. This involves influencing how feedback is designed, delivered, and utilised, rather than passively consuming outputs. For example, learners might decide the type of feedback they need, the delivery medium (e.g. written or chatbot), and how they will act on it. In contrast, a non-shared agency scenario would involve GenAI generating feedback independently, with learners passively receiving it without customising or engaging with the process.

Pedagogical framework for hybrid intelligent feedback

In this section, we present a pedagogical framework for hybrid intelligent feedback (see Figure 5). This framework illustrates a structured process for implementing a hybrid-intelligent feedback approach, integrating both human and GenAI contributions. Below is an elaboration of each stage in the process:

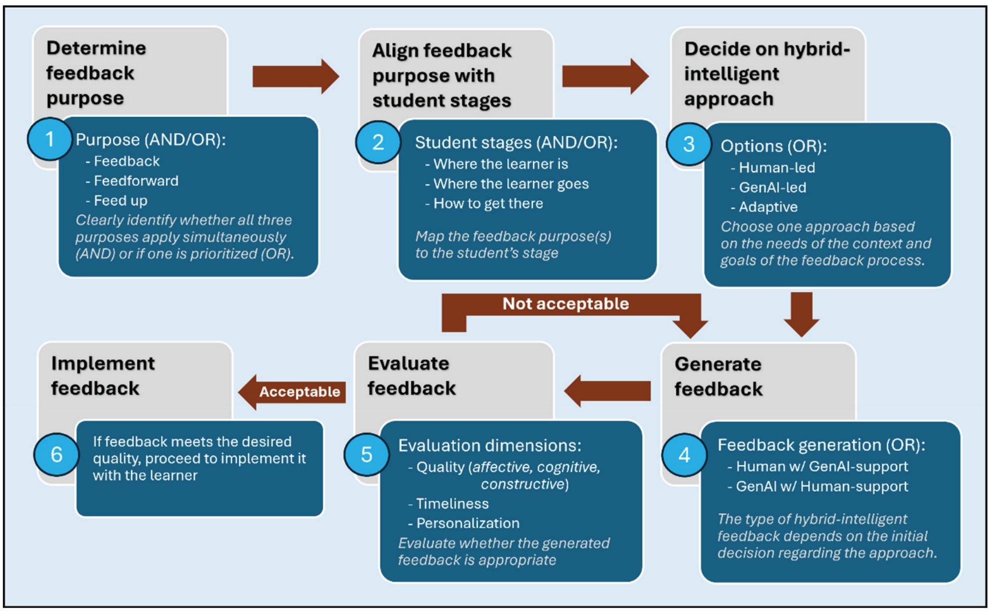

Figure 5. Pedagogical framework for hybrid intelligent feedback.

(1) ***Determine feedback purpose***: Clearly defining the purpose of feedback is the first and essential step for effective hybrid intelligent feedback. This step focuses on selecting feedback (providing insights about current performance), feedforward (offering guidance on future improvements), and feed-up (clarifying goals and expectations). Multiple aspects could be applied simultaneously to provide the learner with complete feedback (AND), or one aspect could be prioritised based on the contextual situation (OR). Example: In a university writing course, a professor employs hybrid intelligent feedback to enhance students' academic writing. As

a first step, the professor may choose to integrate all three feedback types – feedback, feedforward, and feed-up – to support the learning process. This decision may be based on the idea that high-quality feedback often requires a combination of these approaches.

(2) ***Align feedback purpose with student stages***: In this step, the purpose is to make sure that the feedback purposes align with the stages in which students are (or are expected to be). In other words, feedback should be tailored to the learner's stage of development, focusing on: where the learner is (the current level of understanding or skill), where the learner goes (the desired learning outcomes or goals), and how to get there (the steps or strategies needed to achieve the goals). This alignment ensures that feedback is relevant and actionable for the students. Example: The professor justifies the use of specific feedback type for each student by considering students' proficiency levels. For weaker students struggling with argument structure, all three feedback types – feedback, feedforward, and feed-up – may be emphasised to provide comprehensive support. In contrast, for more advanced students, the professor might focus primarily on feedback, highlighting specific weaknesses for refinement.

(3) ***Decide on a hybrid-intelligent approach***: This step involves selecting a suitable feedback approach based on the context and goals of the feedback process. The options include the three approaches for hybrid intelligent feedback (human-led feedback with GenAI support, adaptive human-GenAI feedback, and GenAI-led feedback with human enrichment). Example: In a writing course, the professor might choose a GenAI-led feedback approach for two reasons. First, the large class size makes it difficult for the professor to provide feedback due to a high workload. Second, the feedback for the given class task primarily focuses on writing structure, which GenAI can effectively analyse and assess.

(4) ***Generate feedback***: When decisions have been made on the hybrid intelligent feedback approach, feedback purpose, and its alignment with student stages, it is time to generate the feedback. As discussed above, the feedback generation process depends on the selected hybrid intelligent approach. If it is a human-led feedback approach then initially human takes the role on generating feedback and then using GenAI to support human-generated feedback. If it is GenAI-led feedback, then human agent should prompt with GenAI to generate feedback and then add his/her input to enrich it. Example: The professor provides key prompts to the GenAI system, guiding it to evaluate the writing task's logical coherence, clarity, and language accuracy. Based on these instructions, the GenAI generates detailed feedback, identifying areas for improvement and offering targeted suggestions.

(5) ***Evaluate feedback***: Once feedback is generated, it must be carefully evaluated to ensure its quality, relevance, and effectiveness. The evaluation of the feedback could be done by both GenAI and Human, or in collaboration. There are three key dimensions for quality feedback that should be considered in evaluation: quality, timeliness, and personalisation. Quality encompasses an affective aspect (maintaining an appropriate emotional tone that motivates and encourages learners), multiple cognitive aspects (ensuring accuracy, depth, and clarity), and a constructive aspect (providing actionable guidance for improvement). Timeliness involves delivering the feedback at the right moment to maximise its

impact on learning and performance. Personalisation focuses on tailoring the feedback to the learner's specific needs, goals, and context to make it relevant and meaningful. If the feedback meets these standards, it moves to the next stage for implementation; if not, revisions are required to refine and enhance its quality. Example: The professor reviews and refines GenAI-generated feedback to ensure it aligns with students' needs. For instance, if the professor observes that while the AI-generated feedback is accurate, it lacks nuanced suggestions for strengthening argumentation, they supplement it with additional comments. These refinements make the feedback more constructive, tailored to the student's proficiency level, and actionable for improvement.

(6) ***Implement feedback***: When feedback meets the standards, it is time to implement feedback. This step involves delivering feedback to students. Example: Once the professor has reviewed and refined the GenAI-led feedback, they can implement it by delivering it to students through the university's online learning platform.

This process ensures a systematic and thoughtful approach to hybrid-intelligent feedback, leveraging the strengths of both humans and GenAI while maintaining a focus on student-centered outcomes.

Recommendations for future research on hybrid intelligent feedback

Pedagogical guidelines for hybrid intelligent feedback

One significant direction for future research is developing pedagogical guidelines that teachers can follow when implementing GenAI feedback in classrooms. Current literature highlights a disconnect between GenAI's capabilities and its pedagogical application (Chen et al., 2020; Díaz & Nussbaum, 2024). In the context of hybrid intelligence, these guidelines should address how GenAI can complement human feedback effectively by balancing GenAI's speed and precision with human judgement and empathy (Molenaar, 2022). The establishment of guidelines will help teachers understand when and how to use GenAI feedback effectively, particularly in ways that complement human feedback rather than replace it.

Methodological advancements for hybrid intelligent feedback

While existing GenAI feedback systems can perform structured tasks, methodological research is required to enhance GenAI's ability to provide high-quality, contextualised feedback, particularly in collaboration with human feedback. This would involve improving GenAI's algorithms to better mimic the nuanced, reflective processes inherent in human feedback (Binz & Schulz, 2023). Hybrid intelligence systems could incorporate adaptive algorithms that align GenAI-generated feedback with specific learner profiles, ensuring that the feedback remains relevant and personalised (Molenaar, 2022).

Exploring human-GenAI collaboration in feedback

Research on human-GenAI collaboration in feedback is essential to fully harness the strengths of both GenAI and human contributors. While we took initial steps to conceptualise and outline feedback in hybrid intelligence systems, more research is needed in this regard. Hybrid intelligence frameworks emphasise not only the division of tasks but also the co-evolution of roles, where humans and GenAI dynamically adapt their contributions based on the complexity of feedback requirements (Molenaar, 2022). Investigating how hybrid intelligence can effectively integrate the analytical precision of GenAI with the experiential and emotional insights of human feedback providers is crucial. We recommend attention to specific essential elements of feedback (quality, timeliness, and personalisation). For example, complex forms of integration could make teacher feedback even less timely, rather than more timely, or less personalised rather than more personalised. This research can lead to innovative, integrated feedback practices that optimise the unique capabilities of both human and GenAI agents.

Hybrid intelligent feedback literacy

To maximise the benefits of hybrid intelligent feedback, future research should address the importance of such feedback literacy among students. Hybrid intelligent feedback literacy involves understanding how to interpret, question, and apply GenAI feedback effectively in collaboration with human feedback. Within hybrid intelligence, literacy extends to understanding the complementary nature of GenAI and human feedback, empowering students to critically evaluate both sources and make informed decisions about their learning strategies (Molenaar, 2022). Studies could investigate interventions that train students to distinguish between feedback suitable for immediate implementation versus feedback requiring further validation by human instructors. This approach will empower students to engage with hybrid intelligent feedback critically, fostering autonomous learning and enhancing the feedback's overall educational value.

Regulation of learning with hybrid intelligent feedback

A promising research area involves exploring how hybrid intelligent feedback can support self-regulated learning. While teacher feedback often emphasises this aspect, and peer and self-feedback are shown to enhance it, overly detailed GenAI feedback risks undermining students' self-regulation. A hybrid intelligent feedback approach can play a critical role by blending GenAI's precise recommendations with human feedback to encourage reflective and metacognitive engagement (Molenaar, 2022). Tailored GenAI feedback could further promote metacognitive awareness, helping students set goals, monitor progress, and adjust strategies using data-driven insights (Afzaal et al., 2024). Beyond individual self-regulation, the broader question of how teachers should support students in a GenAI-integrated classroom arises. As GenAI feedback tools become more common, teachers' roles must adapt to mediate between AI-generated insights and students' personalised learning needs (Molenaar, 2022). Research should explore strategies for teaching students to use GenAI feedback responsibly, including recognising potential errors, evaluating feedback quality, and learning from feedback rather than blindly implementing it. This aligns with the need to redefine teacher roles in hybrid intelligence systems to foster meaningful and effective learning.

Ethical considerations and trust in hybrid intelligent feedback

As hybrid intelligent feedback becomes more common, ethical concerns must be carefully addressed (Nguyen et al., 2023). Future research should explore transparency, accountability, and privacy in using feedback in hybrid intelligence systems (Markauskaite et al., 2022). In addition, hybrid intelligence systems must incorporate explainable AI techniques that allow students and teachers to understand the rationale behind GenAI feedback, fostering trust and transparency (Molenaar, 2022). Research should examine methods to meaningfully earn trust in GenAI feedback, potentially by developing GenAI feedback systems that allow students to ask follow-up questions or access explanations, thereby fostering a more transparent and interactive feedback process.

Conclusion

This paper offers valuable insights into the concept of GenAI feedback by presenting a definition grounded in Hattie and Timperley's (2007) feedback framework and formative assessment theory (Black & Wiliam, 2009). It further explores the role of GenAI feedback both as a standalone source and as hybrid intelligent feedback in collaboration with humans, aligning with Molenaar's (2022) vision of hybrid intelligence – where human-AI collaboration achieves outcomes beyond their individual capabilities. The paper introduces three primary approaches to hybrid intelligent feedback: Human-Led Feedback with GenAI Support, Adaptive Human-GenAI Feedback, and GenAI-Led Feedback with Human Enrichment. Each approach delineates distinct roles for humans and GenAI in generating feedback, emphasising their complementary strengths. Building on this, the paper proposes a pedagogical framework that outlines practical steps for implementing hybrid intelligent feedback in educational contexts. Lastly, it offers recommendations for future research, highlighting key areas to further refine and expand the understanding of hybrid intelligent feedback. This paper represents an initial step towards the conceptualisation of hybrid intelligent feedback in education, contributing to the existing literature by advancing theoretical insights, proposing practical frameworks, and paving the way for innovative research and practice in the field.

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Notes on contributors

Seyyed Kazem Banihashem is an Assistant Professor of Educational Technology at the Open University of the Netherlands.

Omid Noroozi is an Associate Professor of Educational Technology at Wageningen University and Research, the Netherlands.

Hassan Khosravi is an Associate Professor of data science and learning analytics at the University of Queensland, Australia.

Christian D. Schunn is a Professor of Psychology and Senior Scientist in the Learning Research and Development Center at the University of Pittsburgh, USA.

Hendrik Drachsler is a Professor of Educational Technology at DIPF Leibniz Institute for Research and Information in Education and the Open University of the Netherlands.

ORCID

Seyyed Kazem Banihashem http://orcid.org/0000-0002-9978-3783
Omid Noroozi http://orcid.org/0000-0002-0622-289X
Hassan Khosravi http://orcid.org/0000-0001-8664-6117
Christian D. Schunn http://orcid.org/0000-0003-3589-297X
Hendrik Drachsler http://orcid.org/0000-0001-8407-5314

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